

COURSE OVERVIEW IT0039 Batch Normalization

CEUS

(30 PDHs)

<u>Course Title</u> Batch Normalization

Course Date/Venue

Session 1: August 03-07, 2025/Tamra Meeting Room, Al Bandar Rotana Creek, Dubai UAE

Session 2: November 17-21, 2025/Glasshouse Meeting Room, Grand Millennium Al Wahda Hotel, Abu Dhabi, UAE

Course Reference

IT0039

Course Duration/Credits

Five days/3.0 CEUs/30 PDHs

Course Description









This course is designed to provide participants with a detailed up-to-date overview and of Batch Normalization. It covers the vanishing and exploding gradient problems and the effects of poorly scaled inputs on training stability; the normalization techniques and batch normalization as an alternative to input normalization; the mathematics behind batch normalization; the batch normalization in different layers of neural networks; how batch normalization reduces covariate shift and reducing the sensitivity to learning rate selection; the generalization and reducing overfitting; and the batch normalization and activation functions.

Further, the course will also discuss the batch normalization in convolutional neural networks (CNNs) and recurrent neural networks (RNNs) and transformers; the layer normalization versus batch normalization: the instance normalization and group normalization: the difference between batch normalization, weight normalization and the need for batch renormalization in certain applications; handling very small or large batch sizes; and the impact of minibatch size on normalization statistics.



IT0039 - Page 1 of 9





During this interactive course, participants will learn the batch normalization in object detection models, generative adversarial networks (GANs) and reinforcement learning (RL); the impact of batch normalization in large-scale datasets including hyperparameter tuning for batch normalization; the evolution of normalization beyond batch normalization and emerging alternatives like normalizer-free networks; and handling batch normalization in real-world inference, converting batch norm layers to fixed scaling and optimizing batch norm for mobile and edge devices

Course Objectives

Upon the successful completion of this course, each participant will be able to:-

- Apply and gain a comprehensive knowledge on batch normalization
- Identify vanishing and exploding gradient problems and the effects of poorly scaled inputs on training stability
- Carryout normalization techniques and batch normalization as an alternative to input normalization
- Discuss the mathematics behind batch normalization including batch normalization in different layers of neural networks
- Explain how batch normalization reduces covariate shift and reduce the sensitivity to learning rate selection
- Improve generalization and reducing overfitting and identify batch normalization and activation functions
- Describe batch normalization in convolutional neural networks (CNNs) and recurrent neural networks (RNNs) and transformers
- Differentiate layer normalization versus batch normalization and apply instance normalization and group normalization
- Explain the difference between batch normalization and weight normalization and the need for batch renormalization in certain applications
- Handle very small or large batch sizes and identify the impact of mini-batch size on normalization statistics
- Illustrate batch normalization in object detection models, generative adversarial networks (GANs) and reinforcement learning (RL)
- Recognize the impact of batch normalization in large-scale datasets including hyperparameter tuning for batch normalization
- Discuss the evolution of normalization beyond batch normalization and emerging alternatives like normalizer-free networks
- Handle batch normalization in real-world inference, converting batch norm layers to fixed scaling and optimizing batch norm for mobile and edge devices

Exclusive Smart Training Kit - H-STK®



Participants of this course will receive the exclusive "Haward Smart Training Kit" (**H-STK**[®]). The **H-STK**[®] consists of a comprehensive set of technical content which includes **electronic version** of the course materials conveniently saved in a **Tablet PC**.



IT0039 - Page 2 of 9





Who Should Attend

This course provides an overview of all significant aspects and considerations of batch normalization for machine learning practitioners and engineers, software engineers working with ai, data scientists, Al/deep learning researchers, students and learners in deep learning and other technical staff.

Course Certificate(s)

Internationally recognized certificates will be issued to all participants of the course who completed a minimum of 80% of the total tuition hours.

Certificate Accreditations

Certificates are accredited by the following international accreditation organizations: -

- BAC
 - British Accreditation Council (BAC)

Haward Technology is accredited by the **British Accreditation Council** for **Independent Further and Higher Education** as an **International Centre**. BAC is the British accrediting body responsible for setting standards within independent further and higher education sector in the UK and overseas. As a BAC-accredited international centre, Haward Technology meets all of the international higher education criteria and standards set by BAC.

Haward Technology Middle East will award **3.0 CEUs** (Continuing Education Units) or **30 PDHs** (Professional Development Hours) for participants who completed the total tuition hours of this program. One CEU is equivalent to ten Professional Development Hours (PDHs) or ten contact hours of the participation in and completion of Haward Technology programs. A permanent record of a participant's involvement and awarding of CEU will be maintained by Haward Technology. Haward Technology will provide a copy of the participant's CEU and PDH Transcript of Records upon request.

 The International Accreditors for Continuing Education and Training (IACET - USA)

Haward Technology is an Authorized Training Provider by the International Accreditors for Continuing Education and Training (IACET), 2201 Cooperative Way, Suite 600, Herndon, VA 20171, USA. In obtaining this authority, Haward Technology has demonstrated that it complies with the **ANSI/IACET 2018-1 Standard** which is widely recognized as the standard of good practice internationally. As a result of our Authorized Provider membership status, Haward Technology is authorized to offer IACET CEUs for its programs that qualify under the **ANSI/IACET 2018-1 Standard**.

Haward Technology's courses meet the professional certification and continuing education requirements for participants seeking **Continuing Education Units** (CEUs) in accordance with the rules & regulations of the International Accreditors for Continuing Education & Training (IACET). IACET is an international authority that evaluates programs according to strict, research-based criteria and guidelines. The CEU is an internationally accepted uniform unit of measurement in qualified courses of continuing education.



IT0039 - Page 3 of 9





Course Instructor(s)

This course will be conducted by the following instructor(s). However, we have the right to change the course instructor(s) prior to the course date and inform participants accordingly:



Mr. Mohamed Radwan, PMP, CCNA, CCNP, CCSD, CCDA, Solaris, IBM, ITIL, NetApp, Symantec, MS, is a Senior IT Engineer & Project Manager with over 25 years of teaching and industrial experience in IT Continuity Management, Continuity Management Lifecycle, Continuity Plans Development & Implementation, IT Risk Assessment & Impact Analysis, Effective Crisis Management Structure, IT Networking & Project Management. His main expertise covers Network Security, Physical Security, Effective E-Communication &

Collaboration Skills, Information Confidentiality, Data Confidentiality Classification, IT Risk Management Concepts, IT Project Management, IT Confidentiality, Security Protocols, IT Security Policies, Security Practices, Security Solutions, IT Network Security Administration, IT Service Management, Telecom, Datacom & Network, IP PBX/PABX, IT Management, IT System, System Administration, SIGMA IT, Microsoft, Data Centre Analysis & Design, CISCO, CCNA, CCNP, CCSP & CCDA, NetAPP, Netbackup, Symantec, SUN Storage, IBM Storage, SAN Switches, SUN Blades, Tape Library, Data Storage & Protection, Platforms, Data Base, Networking, Security Communication Equipments, Servers **Cross-Platform** Systems, Integration Technologies, Middleware, Switch & Routers Installation & Design, Backup Solution Installation and Network Infrastructure & System Upgrade. Further, he is also wellversed in ITIL Foundation, Project Analysis, Project Management and Project Implementation. He is currently the Regional Support & Services Manager of the STME that provides the Middle East Regional information infrastructure solutions, and at the same time, he is the Data Protection & Storage Consultant for various international telecommunications companies.

During his career life, Mr. Mohamed has gained his technical and practical expertise through a variety of challenging and key positions such as the **Regional Support & Services Manager**, **Network/Security Consultant**, **Data Protection & Storage Consultant**, **Accounts Manager**, **Project Manager**, **Symantec Trainer & Administrator**, **Network Branch Manager**, **Technical Support Manager**, **Training Manager**, **IT Continuity Management Specialist**, **IT Trainer** and **Network & Computer Engineer** for various international companies such as the National Organization for Social Insurance (NOSI), USA Aid (ESED), Misr Computer Network & Co. and Informix System.

Mr. Mohamed has a **Bachelor** degree in **Electronics & Communications Engineering**. Further. he is Certified Instructor/Trainer. Certified Internal а а Verifier/Assessor/Trainer by the Institute of Leadership and Management (ILM), a Certified Systems Engineer & Systems Administrator (Security, Microsoft Office Specialist and Microsoft Certified IT Professional), a Certified CISCO Specialist, an Accredited NetApp Storage Architect Professional, a Certified NetApp Backup & **Recovery Implementation Engineer**, a Certified NetApp Data Management Administrator, a Certified NetApp SAN Implementation Engineer, a Certified Symantec Technical Specialist, a Solaris 10 Certified and a Certified IBM Specialist & Systems Expert. Moreover, he is a member of Project Management Institute (PMI), a Chapter member of MENA and has delivered numerous trainings, conferences and workshops worldwide.



IT0039 - Page 4 of 9





Training Methodology

All our Courses are including **Hands-on Practical Sessions** using equipment, State-ofthe-Art Simulators, Drawings, Case Studies, Videos and Exercises. The courses include the following training methodologies as a percentage of the total tuition hours:-

30% Lectures20% Practical Workshops & Work Presentations30% Hands-on Practical Exercises & Case Studies20% Simulators (Hardware & Software) & Videos

In an unlikely event, the course instructor may modify the above training methodology before or during the course for technical reasons.

Course Fee

US\$ 5,500 per Delegate + **VAT**. This rate includes H-STK[®] (Haward Smart Training Kit), buffet lunch, coffee/tea on arrival, morning & afternoon of each day.

Accommodation

Accommodation is not included in the course fees. However, any accommodation required can be arranged at the time of booking.

Course Program

The following program is planned for this course. However, the course instructor(s) may modify this program before or during the course for technical reasons with no prior notice to participants. Nevertheless, the course objectives will always be met:

| Day 1 |
|-------|
|-------|

| Day I | |
|-------------|--|
| 0730 - 0800 | Registration & Coffee |
| 0800 - 0815 | Welcome & Introduction |
| 0815 - 0830 | PRE-TEST |
| 0830 - 0930 | Understanding Neural Network Optimization Challenges The Vanishing and Exploding Gradient Problems • Internal Covariate Shift: Why It Slows Down Learning • Effects of Poorly Scaled Inputs on Training Stability • The Role of Activation Functions in Gradient Flow |
| 0930 - 0945 | Break |
| 0945 – 1045 | <i>Introduction to Normalization Techniques</i> <i>Why Normalization is Essential in Deep Learning</i> • <i>Feature Scaling versus</i> <i>Normalization</i> • <i>Differences Between Data Normalization and Activation</i> <i>Normalization</i> • <i>Overview of Standard Normalization Techniques (Min-Max, Z-score)</i> |
| 1045 - 1145 | What Is Batch Normalization? The Concept of Normalizing Activations in Deep Networks • Batch Normalization as an Alternative to Input Normalization • Effects of Batch Normalization on Gradient Updates • The Role of Learnable Parameters (Gamma and Beta) |
| 1145 - 1230 | The Mathematics Behind Batch NormalizationNormalizing Activations: Mean and Variance Computation • Introducing Scale (γ) and Shift (β) Parameters • Moving Average for Stable Normalization inInference Mode • Effect on Backpropagation and Weight Updates |
| 1230 - 1245 | Break |



IT0039 - Page 5 of 9

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| | Batch Normalization in Different Layers of Neural Networks |
|-------------|---|
| 1245 - 1330 | Applying Batch Normalization After Fully Connected Layers • Batch |
| | Normalization in Convolutional Neural Networks (CNNs) • Normalization in |
| | Recurrent Neural Networks (RNNs) • Case Study: Image Classification with |
| | Batch Normalization |
| | Hands-On: Implementing Batch Normalization in a Simple Neural |
| 1220 1420 | Network |
| | Setting Up TensorFlow and PyTorch Environments • Implementing Batch |
| 1550 - 1420 | Normalization in a Simple MLP (Multi-Layer Perceptron) • Comparing Model |
| | Performance With and Without Batch Normalization • Visualizing Activation |
| | Distributions Using Histograms |
| | Recap |
| 1420 - 1430 | Using this Course Overview, the Instructor(s) will Brief Participants about the |
| | Topics that were Discussed Today and Advise Them of the Topics to be Discussed |
| | Tomorrow |
| 1430 | Lunch & End of Day One |

Day 2

| <u></u> | |
|-------------|---|
| | Speeding Up Training with Batch Normalization |
| 0730 – 0830 | How Batch Normalization Reduces Covariate Shift • Improved Convergence Rate |
| | and Training Stability • Reducing the Sensitivity to Learning Rate Selection • |
| | Case Study: Faster Convergence in Deep Networks |
| | Improving Generalization & Reducing Overfitting |
| 0830 0030 | Effect of Batch Normalization on Regularization • Why Batch Normalization |
| 0850 - 0950 | Reduces the Need for Dropout • The Role of Batch Normalization in Large-Scale |
| | Models • Comparing Overfitting Levels With and Without Batch Normalization |
| 0930 - 0945 | Break |
| | Batch Normalization & Activation Functions |
| | How Batch Normalization Interacts with ReLU, Leaky ReLU, and Sigmoid • |
| 0945 - 1130 | Batch Normalization versus Batch Scaling in Deep Networks • Avoiding Dead |
| | Neurons in Activation Layers • Case Study: Training Stability in ResNets and |
| | DenseNets |
| | Batch Normalization in Convolutional Neural Networks (CNNs) |
| 1130 1230 | Where to Apply Batch Normalization in CNNs • Batch Normalization and |
| 1130 - 1230 | Feature Extraction Layers • Effect on Object Detection and Image Segmentation |
| | • Case Study: Performance Gain in VGG, ResNet, and MobileNet |
| 1230 - 1245 | Break |
| | Batch Normalization in Recurrent Neural Networks (RNNs) & |
| | Transformers |
| 1045 1220 | The Challenge of Applying Batch Normalization in RNNs • Why Layer |
| 1245 - 1550 | Normalization is Preferred Over Batch Normalization in NLP • Batch |
| | Normalization in Transformers and Attention Mechanisms • Case Study: Batch |
| | Normalization in Machine Translation Models |
| | Hands-On: Implementing Batch Normalization in CNNs |
| 1330 - 1420 | Building a CNN Model with Batch Normalization in PyTorch • Comparing |
| 1330 - 1420 | Performance With Standard CNN Models • Evaluating Convergence Speed and |
| | Loss Reduction • Visualizing Feature Maps Before and After Normalization |
| | Recap |
| 1420 – 1430 | Using this Course Overview, the Instructor(s) will Brief Participants about the |
| | Topics that were Discussed Today and Advise Them of the Topics to be Discussed |
| | Tomorrow |
| 1430 | Lunch & End of Day Two |
| | |



IT0039-08-25|Rev.00|02 April 2025

IT0039 - Page 6 of 9

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| Day 3 | |
|-------------|---|
| 0730 - 0830 | <i>Layer Normalization versus Batch Normalization</i> Why Batch Normalization May Not Work Well in Some Cases • Understanding Layer Normalization and its Differences • When to Use Layer Normalization Instead of Batch Normalization • Case Study: NLP Tasks Using Layer Normalization |
| 0830 - 0930 | <i>Instance Normalization & Group Normalization</i> <i>Instance Normalization for Style Transfer and GANs</i> • <i>Group Normalization for</i> <i>Small Batch Sizes</i> • <i>How Instance Normalization Differs from Batch</i> <i>Normalization</i> • <i>Case Study: Instance Normalization in Image Generation</i> <i>Models</i> |
| 0930 - 0945 | Break |
| 0945 – 1130 | Batch Normalization versus Weight Normalization The Concept of Weight Normalization in Neural Networks • Effect of Weight Normalization on Model Training • Comparison of Batch Normalization and Weight Normalization • When to Use Weight Normalization Instead of Batch Normalization |
| 1130 - 1230 | Batch Renormalization – Fixing Small Batch Size Issues Need for Batch Renormalization in Certain Applications • How Batch Renormalization Addresses Training Issues • Moving Averages in Batch Renormalization • Case Study: Application in Low-Data Regimes |
| 1230 - 1245 | Break |
| 1245 - 1330 | Challenges of Batch Normalization in Practical Applications Handling Very Small or Large Batch Sizes • The Impact of Mini-Batch Size on Normalization Statistics • Understanding Batch Normalization in Transfer Learning • Strategies for Handling Batch Normalization in Fine-Tuning |
| 1330 - 1420 | Hands-On: Implementing Different Normalization Techniques Implementing Layer Normalization and Group Normalization • Comparing the Impact of Various Normalization Techniques • Training a Model With and Without Normalization • Analyzing Differences in Training Speed and Model Accuracy |
| 1420 - 1430 | Recap Using this Course Overview, the Instructor(s) will Brief Participants about the Topics that were Discussed Today and Advise Them of the Topics to be Discussed Tomorrow |
| 1430 | Lunch & End of Day Three |

Day 4

| | Batch Normalization in Object Detection Models |
|-------------|---|
| 0730 - 0830 | Role of Batch Normalization in YOLO, Faster R-CNN, and SSD • How |
| | Normalization Improves Object Detection Accuracy • Impact of Normalization |
| | on Model Convergence • Case Study: YOLO With and Without Batch |
| | Normalization |
| 0830 - 0930 | Batch Normalization in Generative Adversarial Networks (GANs) |
| | Why Normalization is Crucial for GAN Training Stability • Using Batch |
| | Normalization in Discriminators and Generators • Normalization in Conditional |
| | GANs for Image Synthesis • Case Study: DCGAN With Batch Normalization |
| 0930 - 0945 | Break |
| 0945 - 1130 | Batch Normalization in Reinforcement Learning (RL) |
| | How Normalization Helps in Policy Gradient Methods • Batch Normalization in |
| | Deep Q-Networks (DQN) • Normalization for Stable Training in Actor-Critic |
| | Methods • Case Study: Normalization in OpenAI Gym Environments |

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IT0039 - Page 7 of 9



| | Impact of Batch Normalization in Large-Scale Datasets |
|-------------|---|
| 1130 - 1230 | How Batch Normalization Improves Training on ImageNet • Normalization in |
| | Deep Architectures Like EfficientNet • Scaling Up Deep Learning Models With |
| | Batch Normalization • Case Study: Batch Normalization in ResNet-50 vs. |
| | ResNet-101 |
| 1230 - 1245 | Break |
| | Hyperparameter Tuning for Batch Normalization |
| 1245 - 1330 | Adjusting Learning Rate for Models With Batch Normalization • Effect of Batch |
| | Normalization on Weight Initialization • Choosing the Right Place to Apply |
| | Batch Normalization • Best Practices for Combining Batch Normalization and |
| | Dropout |
| | Hands-On: Applying Batch Normalization in Large-Scale Models |
| 1330 - 1420 | Training ResNet with Batch Normalization on ImageNet • Analyzing Gradient |
| | Flow and Convergence Speed • Evaluating Performance Across Different |
| | Normalization Strategies • Fine-Tuning Hyperparameters for Optimal Results |
| 1420 – 1430 | Recap |
| | Using this Course Overview, the Instructor(s) will Brief Participants about the |
| | Topics that were Discussed Today and Advise Them of the Topics to be Discussed |
| | Tomorrow |
| 1430 | Lunch & End of Day Four |

Day 5

| | Future Research in Normalization Techniaues |
|-------------|---|
| | Evolution of Normalization Beyond Batch Normalization • Emerging |
| 0730 – 0930 | Alternatives Like Normalizer-Free Networks • Self-Normalizing Neural |
| | Networks (SNNs) • Case Study: The Future of Normalization-Free Deep |
| | Learning |
| 0930 - 0945 | Break |
| | Deploying Models with Batch Normalization |
| 0045 1120 | Handling Batch Normalization in Real-World Inference • Converting Batch |
| 0945 - 1130 | Norm Layers to Fixed Scaling • Optimizing Batch Norm for Mobile and Edge |
| | Devices • Case Study: Deploying Batch Normalized Models on TensorFlow Lite |
| | Hands-On Final Project: Building an End-to-End Deep Learning Model |
| 1120 1220 | with Batch Normalization |
| 1150 - 1250 | Selecting a Dataset and Model Architecture • Implementing Batch |
| | Normalization in a Complex Model |
| 1230 - 1245 | Break |
| | Hands-On Final Project: Building an End-to-End Deep Learning Model |
| 1245 1300 | with Batch Normalization (cont'd) |
| 1245 - 1500 | Comparing Training Performance With and Without Batch Normalization • |
| | Deploying and Evaluating the Model in Production |
| | Course Conclusion |
| 1300 – 1315 | Using this Course Overview, the Instructor(s) will Brief Participants about the |
| | Course Topics that were Covered During the Course |
| 1315 – 1415 | POST TEST |
| 1415 - 1430 | Presentation of Course Certificates |
| 1430 | Lunch & End of Course |



IT0039 - Page 8 of 9

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Practical Sessions

This practical and highly-interactive course includes real-life case studies and exercises:-



Course Coordinator

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